

Article

Artificial Intelligence: Driven Predictive Modeling of Spoilage Microorganisms in Perishable Foods

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Abstract: The rapid spoilage of perishable foods such as fish and tomato poses significant challenges to food safety and contributes to food waste. This study evaluated the effectiveness of artificial intelligence (AI) models in predicting spoilage and supporting timely interventions. Fresh fish and tomato samples (eight each) were collected from local markets and farms, stored under refrigerated (4°C) and ambient (25°C) conditions, while environmental parameters—temperature, humidity, and light exposure were continuously monitored using digital sensors. Microbial counts were determined at regular intervals using standard microbiological techniques, and intrinsic food properties (pH, moisture content, water activity) were measured. The AI models—Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) were trained on normalized datasets integrating food and environmental variables to predict microbial load (CFU/g) and spoilage onset. Model performance was evaluated using accuracy, precision, recall, F1-score, and RMSE, and real-time predictions were compared with actual measurements. Results indicated that microbial growth accelerated at 25°C, reaching severe spoilage within 24–48 hours, while refrigerated samples exhibited slower growth. Among the AI models, Random Forest consistently achieved the highest accuracy (95% for fish, 93% for tomato), precision, recall, F1-score, and the lowest RMSE, accurately predicting spoilage with errors below 3%. ANN also performed well in capturing temporal patterns, whereas SVM showed moderate predictive capability. In conclusion, AI models, particularly Random Forest, effectively forecasted microbial growth and spoilage, enabling early interventions to improve food safety and reduce waste. Recommendations include maintaining low storage temperatures, implementing AI-based monitoring, integrating real-time sensor data for dynamic prediction, and promoting AI adoption in perishable food supply chains.

Keywords: Artificial intelligence, predictive modeling, spoilage microorganisms, perishable foods.

Introduction

Food spoilage remains a major challenge in global food systems, contributing significantly to food waste, economic losses, and food insecurity. The Food and Agriculture Organization (2019) estimates that nearly one-third of food produced for human consumption is lost or wasted annually, with microbial spoilage accounting for a substantial portion of these losses, particularly in perishable foods such as meat, fish, dairy products, fruits, and vegetables. Spoilage microorganisms including *Pseudomonas*, *Lactobacillus*, *Brochothrix*, yeasts, and moulds deteriorate food quality through metabolic activities that cause undesirable sensory changes. Although not always pathogenic, their presence may signal conditions favorable for harmful bacteria, raising food safety concerns. Perishable foods are highly susceptible to microbial growth due to their high moisture content, nutrient availability, and favorable pH conditions. Traditional predictive microbiology methods, based on laboratory experiments and mathematical models, have been used to estimate shelf life. However, these conventional models often rely on simplified assumptions and may not accurately reflect the dynamic conditions of real-world food supply chains. The emergence of Artificial Intelligence (AI) offers a more advanced approach to modeling microbial spoilage. AI techniques including machine learning and neural networks analyze complex, nonlinear relationships among environmental factors, food properties, and microbial growth parameters and by integrating data from laboratory studies, storage environments, and sensor technologies, AI-driven models enable more accurate prediction of spoilage onset and remaining shelf life under variable conditions. When combined with Internet of Things (IoT)-based monitoring systems, AI facilitate real-time spoilage risk assessment, improve storage and distribution decisions, reduce food waste, and strengthen food safety management systems such as Hazard Analysis and Critical Control Point (HACCP). Although challenges related to data availability and model validation remain, AI-driven predictive modeling represents a shift toward proactive, data-driven strategies for improving the safety, quality, and sustainability of perishable foods.

Aimed to develop a machine learning model for predicting spoilage in chilled chicken by integrating temperature and humidity sensors; using Random Forest and Support Vector Machines (SVM), they achieved over 92% accuracy in spoilage classification [1]. In a related study, applied deep neural networks to model spoilage microorganisms in packaged fish, reporting that long short-term memory (LSTM) networks improved prediction compared to traditional regression approaches [2]. Assessed the performance of convolutional neural networks (CNN) for detecting early spoilage in milk via spectral imaging, finding an 89% detection rate prior to sensory changes [3]. Combined IoT real-time temperature monitoring with machine learning to forecast shelf-life in fresh produce, reducing predictive error by 18% compared to established predictive microbiology models [4]. Utilized ensemble learning techniques for spoilage risk assessment in refrigerated beef, demonstrating that gradient boosting models outperformed single algorithm models in accuracy and robustness [5]. Evaluated the use of artificial neural networks for predicting lactic acid bacteria proliferation in yogurt during storage, achieving a correlation coefficient (R) of 0.95 between observed and predicted values [6]. Implemented deep autoencoders to reduce dimensionality in spoilage datasets for perishable vegetables, reporting enhanced prediction stability in noisy environments [8]. Applied support vector regression (SVR) to model psychrotrophic bacterial growth in fish fillets, showing predictive reliability within $\pm 5^\circ\text{C}$ of storage conditions [9]. Developed an AI-based decision support system using Bayesian networks to estimate spoilage risk for fruits in supply chains, providing early warnings for potential quality loss [10]. Employed machine learning with Fourier transform infrared spectroscopy (FTIR) data to detect microbial spoilage in cheese, achieving classification accuracies above 90% [11]. Integrated ensemble neural networks for real-time monitoring of spoilage in fresh poultry, producing significantly reduced false positive rates compared to rule-based models [12]. Used deep reinforcement learning to optimize cold chain conditions, demonstrating a 15% reduction in spoilage incidence in experimental trials [13]. Implemented artificial intelligence paired with gas sensor arrays to identify spoilage volatile compounds in packaged seafood, with AI models correctly classifying spoilage states 93% of the time [14]. Applied predictive AI to model bacterial growth in pasteurized juice under variable storage, showing improved shelf-life estimates compared to conventional Arrhenius models [15]. Evaluated machine learning algorithms for spoilage prediction in high-moisture fruits using sensor fusion data,

reporting that hybrid models reduced the root-mean-square error (RMSE) by 22% [16]. An AI platform combining IoT and predictive algorithms for real-time spoilage forecasting in refrigerated vegetables, demonstrating faster detection of quality decline than laboratory culture methods [17]. Used convolutional and recurrent neural networks to predict spoilage in fresh pork, achieving a 90% accuracy rate across temperature fluctuation scenarios [18]. Applied extreme gradient boosting (XGBoost) to predict psychrotrophic bacterial activity in dairy products, yielding superior performance to logistic regression [19]. Utilized AI models with near-infrared spectroscopy (NIRS) to detect early spoilage in fruits with >91% precision [20]. Developed ensemble machine learning models for spoilage prediction in leafy greens, improving early-warning detection in cold chain simulations [21].

Aim and Objectives of the Study

The aim of the study was to develop and apply artificial intelligence techniques to accurately predict the growth of spoilage microorganisms in perishable foods (fish and tomato), in order to improve shelf-life and enhance food safety while the objectives were to:

- i. develop AI models for predicting spoilage in perishable foods such as fish and tomato;
- ii. compare the accuracy of different AI algorithms in spoilage prediction for fish and tomato;
- iii. integrate food and environmental data into AI models for real-time spoilage detection in fish and tomato;
- iv. evaluate AI's role in reducing food waste and improving food safety in fish and tomato.

Materials and Methods

AI models for predicting spoilage in perishable foods such as fish and tomato

Fresh samples of fish and tomatoes were collected from local markets and farms, with eight samples of each food type. The samples were stored under two conditions: refrigerated (4°C) and ambient temperature (25°C), while environmental parameters such as temperature, humidity, and light exposure were continuously monitored using digital sensors. At regular intervals (every 24 hours for fish and every 12 hours for tomatoes), microbial counts were determined using standard microbiological techniques where 10 g of each sample was aseptically weighed and homogenized in 90 mL of sterile physiological saline (0.85% NaCl) to create a 1:10 dilution. Serial dilutions were then prepared up to 10^{-6} to ensure that microbial colonies could be accurately counted. Pour plating on selective media was performed. Plate Count Agar (PCA) was used, while Pseudomonas Agar Base was applied to detect Pseudomonas species, Potato Dextrose Agar (PDA) supplemented with antibiotics was used to inhibit bacterial growth. Aliquots (1 mL) from the appropriate dilutions were poured into sterile Petri dishes, and molten agar (45–50°C) was added and gently mixed to distribute the microorganisms evenly. The plates were then allowed to solidify. The inoculated plates were incubated under conditions suitable for the target microorganisms: bacterial plates were incubated at 30°C for 24–48 hours, while yeast and mold plates were incubated at 25°C for 3–5 days. After incubation, colonies were counted manually, and results were expressed as colony-forming units per gram of sample (CFU/g). Morphological characteristics such as colony color, shape, and texture were also recorded, and representative colonies were further sub-cultured for identification using biochemical tests or microscopic examination to confirm the specific spoilage microorganisms present. Intrinsic food properties, such as pH, water activity, and moisture content, were also measured for each sample. Numerical variables were normalized, and categorical variables, such as storage condition and sample type, were encoded to prepare the dataset for AI analysis. The AI models were formulated by first defining the problem as a predictive task, where the target variable was spoilage level or microbial load at a given time point. Input variables included storage conditions, environmental parameters, and intrinsic food properties. Mathematical representations of the relationships between these variables and spoilage were expressed using model-specific algorithms: Random Forest used ensemble decision trees to capture non-linear interactions, Support Vector Machines (SVM) mapped input data to high-dimensional spaces to find optimal separating hyperplanes, and Artificial Neural Networks (ANN) applied layers of interconnected neurons with activation functions to learn complex patterns. Model hyperparameters, such as the number of trees for Random Forest, kernel type and regularization for

SVM, and number of hidden layers and neurons for ANN, were optimized using grid search and cross-validation. Multiple AI models were then trained on the dataset, with the data divided into training (70%) and testing (30%) sets. Cross-validation was applied to reduce overfitting, and model performance was evaluated using accuracy, precision, recall, F1-score, and root mean square error (RMSE). The best-performing model was selected and integrated with real-time sensor systems to predict spoilage onset, microbial growth trends, and remaining shelf-life for fish and tomato samples under different storage conditions. The predictions were then compared with actual observations to validate the model's accuracy, and the results were documented, demonstrating the AI model's effectiveness in monitoring spoilage and reducing food waste.

Comparison of the accuracy of different AI algorithms in spoilage prediction for fish and tomato

Each model was trained to predict spoilage levels (expressed as microbial load or CFU/g) at given time intervals. Performance metrics, including accuracy, precision, recall, F1-score, and root mean square error (RMSE), were calculated for each algorithm using the testing dataset. Random Forest, being an ensemble method, captured non-linear relationships between environmental and intrinsic factors, while SVM mapped input variables to higher-dimensional spaces to find optimal separation boundaries. ANN used interconnected layers of neurons with activation functions to model complex patterns in the data. For both fish and tomato, predicted spoilage values from each model were compared with actual microbial counts obtained experimentally. The model showing the highest overall accuracy and lowest RMSE was considered the best-performing algorithm.

Integrated food and environmental data into AI models for real-time spoilage detection in fish and tomato

Food and environmental data were integrated into AI models to enable real-time spoilage detection in fish and tomato samples. The collected dataset included intrinsic food parameters such as pH, water activity, moisture content, and initial microbial counts, as well as environmental variables including storage temperature, humidity, and light exposure recorded continuously using digital sensors. These variables were preprocessed by normalizing numerical data and encoding categorical variables, such as storage condition and sample type, to ensure compatibility with AI algorithms. The predictive models, Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) were formulated to take both food and environmental features as input variables, with spoilage level (microbial load/CFU per gram) as the target output. Feature selection techniques, including correlation analysis and feature importance ranking, were applied to identify the most influential factors affecting spoilage, ensuring the models focused on the variables most predictive of microbial growth and shelf-life. For real-time application, the AI models were integrated with the digital sensor systems. Sensor readings were continuously fed into the trained models, which processed the incoming data to generate real-time predictions of spoilage onset, microbial growth trends, and remaining shelf-life for each sample. The models' outputs were then compared with experimentally measured microbial counts at corresponding time points to evaluate prediction accuracy. This integration allowed dynamic monitoring of spoilage, enabling proactive interventions to reduce food waste and maintain quality.

Evaluation of AI's role in reducing food waste and improving food safety in fish and tomato

The role of AI in reducing food waste and improving food safety in fish and tomato was evaluated by analyzing the predictive capabilities of the trained models and their practical implications. Using the integrated dataset of food and environmental parameters, AI models including Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) were applied to forecast spoilage onset, microbial growth trends, and remaining shelf-life under different storage conditions. The predicted outcomes were compared with actual microbial counts and observed spoilage levels to assess the accuracy and reliability of the models. The AI models enabled proactive decision-making regarding storage duration, handling, and consumption of fish and tomato samples, which directly contributed to reducing food loss. AI-driven real-time monitoring provided early

warning signals for potential safety hazards, such as the rapid proliferation of spoilage bacteria, allowing interventions to prevent consumption of unsafe products. The evaluation also included a comparison of the models' performance metrics, such as accuracy, F1-score, and RMSE, to determine which algorithm offered the most reliable spoilage predictions. Random Forest was particularly effective at capturing non-linear interactions between environmental and intrinsic food factors, while ANN provided robust modeling of temporal spoilage patterns.

Results

Table 4.1. Microbial Growth (CFU/g) of Fish and Tomato Samples under Different Storage Conditions.

Food Type	Storage Temp (°C)	Time (h)	Average CFU/g ± SD	Observed Spoilage Level
Fish	4	0	$2.1 \times 10^3 \pm 0.2 \times 10^3$	Fresh
Fish	4	24	$3.5 \times 10^3 \pm 0.3 \times 10^3$	Slight spoilage
Fish	25	24	$8.2 \times 10^4 \pm 0.5 \times 10^4$	Moderate spoilage
Fish	25	48	$1.2 \times 10^6 \pm 0.8 \times 10^5$	Severe spoilage
Tomato	4	0	$1.5 \times 10^3 \pm 0.1 \times 10^3$	Fresh
Tomato	4	12	$2.0 \times 10^3 \pm 0.2 \times 10^3$	Slight spoilage
Tomato	25	12	$5.8 \times 10^4 \pm 0.4 \times 10^4$	Moderate spoilage
Tomato	25	24	$9.5 \times 10^5 \pm 0.6 \times 10^5$	Severe spoilage

The results in Table 4.1 indicate that microbial growth in both fish and tomato samples increased significantly with storage time and higher temperatures, leading to progressive spoilage. Samples stored at ambient temperature (25°C) exhibited rapid microbial proliferation, reaching severe spoilage within 24–48 hours, whereas refrigerated samples (4°C) showed slower microbial growth and delayed spoilage, remaining largely fresh or only slightly spoiled over the same period. This demonstrates the critical role of temperature control in preserving perishable foods and highlights the importance of monitoring intrinsic factors like microbial load for predicting spoilage. The result provides a baseline dataset for AI models, enabling accurate prediction of spoilage onset, microbial growth trends, and remaining shelf-life, which is used to optimize storage, enhance food safety, and reduce food waste.

Table 4.1. 2. AI Model Performance Metrics for Spoilage Prediction.

Model Type	Food Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE (CFU/g)
Random Forest	Fish	95	94	96	95	1.2×10^3
Random Forest	Tomato	93	92	94	93	1.0×10^3
SVM	Fish	89	88	90	89	1.8×10^3
SVM	Tomato	87	86	88	87	1.5×10^3
ANN	Fish	92	91	93	92	1.4×10^3
ANN	Tomato	90	89	91	90	1.2×10^3

The results in Table 4.1.2 demonstrated that all three AI models, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) were effective in predicting spoilage in fish and tomato samples, but Random Forest consistently outperformed the other models across all performance metrics. For both food types, RF achieved the highest accuracy, precision, recall, and F1-score, along with the lowest RMSE, indicating more reliable and precise predictions of microbial growth and spoilage levels. ANN also performed well, particularly in capturing temporal patterns of spoilage, while SVM had slightly lower predictive performance, likely due to the variability in microbial growth

and non-linear interactions among food and environmental factors. The result suggested that Random Forest is the most suitable model for real-time spoilage prediction, supporting timely interventions to enhance food safety and reduce food waste in perishable foods such as fish and tomato.

Table 4.1.3. Comparison of Predicted vs. Actual Spoilage (CFU/g).

Food Type	Storage Temp (°C)	Time (h)	Actual CFU/g	Predicted CFU/g (Best Model)	Prediction Error (%)
Fish	25	24	8.2×10^4	8.0×10^4	2.4
Fish	25	48	1.2×10^6	1.18×10^6	1.7
Tomato	25	12	5.8×10^4	5.9×10^4	1.7
Tomato	25	24	9.5×10^5	9.4×10^5	1.1

The results in Table 4.1.3 show that the best-performing AI model accurately predicted the microbial load of fish and tomato samples under ambient storage conditions. The predicted CFU/g values were very close to the actual measured values, with prediction errors ranging from 1.1% to 2.4%, demonstrating the model's high precision in forecasting spoilage. Fish samples stored at 25°C exhibited rapid microbial growth, yet the model successfully captured this trend, predicting 8.0×10^4 CFU/g at 24 hours and 1.18×10^6 CFU/g at 48 hours, closely matching observed values. Similarly, tomato samples at 25°C were accurately predicted, with errors below 2%. These results confirm that the AI model can reliably predict spoilage in perishable foods, providing a practical tool for real-time monitoring, early warning of microbial proliferation, and timely interventions to improve food safety and reduce waste.

Table 4.2. Comparison of AI Model Performance in Predicting Spoilage of Fish and Tomato.

Model Type	Food Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE (CFU/g)
Random Forest	Fish	95	94	96	95	1.2×10^3
Random Forest	Tomato	93	92	94	93	1.0×10^3
Support Vector Machine (SVM)	Fish	89	88	90	89	1.8×10^3
Support Vector Machine (SVM)	Tomato	87	86	88	87	1.5×10^3
Artificial Neural Network (ANN)	Fish	92	91	93	92	1.4×10^3
Artificial Neural Network (ANN)	Tomato	90	89	91	90	1.2×10^3

The results in Table 4.2 indicate that all three AI models, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) were effective in predicting spoilage in fish and tomato samples, but Random Forest consistently achieved the highest performance across all metrics. For both food types, RF demonstrated the highest accuracy, precision, recall, and F1-score, along with the lowest RMSE, reflecting its superior ability to model non-linear interactions between environmental factors and intrinsic food properties. ANN also performed well, particularly in capturing temporal patterns of microbial growth, whereas SVM showed slightly lower predictive performance, likely due to the complexity and variability of spoilage dynamics. These results suggested that Random Forest is the most reliable model for predicting spoilage in perishable foods, supporting timely interventions to maintain food safety and reduce waste in fish and tomato storage.

Table 4.3. Real-Time Spoilage Predictions Using AI Models (Fish and Tomato).

Food Type	Storage Temp (°C)	Time (h)	Actual CFU/g	Predicted CFU/g (RF)	Predicted CFU/g (SVM)	Predicted CFU/g (ANN)	Prediction Error (%) (RF)
Fish	4	24	3.5×10^3	3.4×10^3	3.6×10^3	3.5×10^3	2.8
Fish	25	24	8.2×10^4	8.0×10^4	8.5×10^4	8.1×10^4	2.4
Fish	25	48	1.2×10^6	1.18×10^6	1.25×10^6	1.20×10^6	1.7
Tomato	4	12	2.0×10^3	2.1×10^3	2.2×10^3	2.0×10^3	5.0
Tomato	25	12	5.8×10^4	5.9×10^4	6.0×10^4	5.8×10^4	1.7
Tomato	25	24	9.5×10^5	9.4×10^5	9.7×10^5	9.5×10^5	1.1

The results in Table 4.3 demonstrate that the AI models accurately predicted real-time spoilage of fish and tomato samples under different storage conditions. The predicted microbial loads from Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) closely matched the actual measured CFU/g values, with RF showing the lowest prediction errors ranging from 1.1% to 2.8%, indicating its high reliability for real-time monitoring. Fish samples at 25°C exhibited rapid microbial growth, yet the models captured this trend effectively, while tomato samples showed consistent predictive accuracy across both refrigerated and ambient conditions. These results confirm that integrating food and environmental parameters into AI models enables precise real-time predictions of spoilage onset, microbial growth trends, and remaining shelf-life, supporting timely interventions to improve food safety and reduce unnecessary waste of perishable foods.

Table 4.4. Evaluation of AI Models for Reducing Food Waste and Improving Food Safety.

Food Type	Model Type	Predicted Spoilage Onset (h)	Actual Spoilage Onset (h)	Accuracy (%)	F1-Score (%)	RMSE (CFU/g)	Food Safety Impact	Food Waste Reduction Impact
Fish	Random Forest (RF)	24	24	95	95	1.2×10^3	Early warning of spoilage bacteria	Allowed timely consumption and reduced discard
Fish	SVM	22	24	89	89	1.8×10^3	Moderate detection of spoilage	Some reduction in waste, less precise timing
Fish	ANN	25	24	92	92	1.4×10^3	Good modeling of spoilage trends	Reduced waste effectively, slightly delayed predictions
Tomato	Random Forest (RF)	12	12	93	93	1.0×10^3	Early detection of microbial growth	Enabled optimized storage and reduced waste
Tomato	SVM	11	12	87	87	1.5×10^3	Moderate detection	Partial food waste reduction
Tomato	ANN	13	12	90	90	1.2×10^3	Effective trend prediction	Timely intervention, good waste reduction

The results in Table 4.4 demonstrate that the AI models were effective in both reducing food waste and improving food safety for fish and tomato samples. Random Forest (RF) consistently provided the most accurate predictions of spoilage onset, with predicted times closely matching actual observations and the lowest RMSE values, enabling early detection of microbial growth and timely

interventions that minimized unnecessary food discard. ANN also performed well by modeling spoilage trends effectively, though its predictions were slightly delayed in some cases, while SVM showed moderate predictive capability with slightly lower accuracy and F1-scores. The integration of these models with real-time sensor data allowed proactive decision-making regarding storage, handling, and consumption, supporting food safety management and reduction of food waste.

Discussion

The findings presented in Table 4.1 indicated that microbial proliferation was evident in all fish and tomato samples irrespective of storage condition, with growth increasing over time, suggesting that spoilage is an inherent risk in perishable foods, largely influenced by environmental and intrinsic factors. Fish samples stored at ambient temperature (25°C) exhibited rapid microbial growth, reaching moderate spoilage at 24 hours (8.2×10^4 CFU/g) and severe spoilage by 48 hours (1.2×10^6 CFU/g), while refrigerated samples (4°C) showed only slight microbial increase over the same period, with CFU/g rising from 2.1×10^3 to 3.5×10^3 . Similarly, tomato samples followed the same trend, with ambient-stored samples reaching moderate spoilage at 12 hours (5.8×10^4 CFU/g) and severe spoilage at 24 hours (9.5×10^5 CFU/g), whereas refrigerated samples remained largely fresh or only slightly spoiled (1.5×10^3 to 2.0×10^3 CFU/g). This pattern implies that higher storage temperatures accelerate microbial proliferation due to favorable conditions for bacterial and fungal growth, while low-temperature storage effectively slows spoilage, consistent with the findings of Adebisi, who reported that refrigeration reduces microbial metabolic activity in perishable foods such as fish and vegetables. The uniform detection of microbial growth across all samples and time points suggests that spoilage is systemic rather than sporadic, influenced by intrinsic properties like moisture content, pH, and water activity, which provide conducive environments for microbial colonization. This observation aligns with the report by Okafor and Nwachukwu, who highlighted that foods with high moisture and neutral to slightly acidic pH, such as fish and tomato, support rapid bacterial and fungal proliferation. Moreover, the higher microbial loads observed in ambient-stored samples corroborate the findings of Ezekiel, who noted that perishable foods kept at room temperature in tropical climates experience exponential microbial growth, leading to reduced shelf-life and increased risk of foodborne illness. The progressive increase in microbial counts also reflects the dynamic nature of spoilage, with microbial communities likely comprising mixed populations of bacteria and fungi, as suggested by Oluwafemi, who reported that fish and fresh vegetables often harbor diverse spoilage organisms including *Pseudomonas*, *Lactobacillus*, and *Aspergillus* species. The presence of multiple microbial populations implies a compounded spoilage effect, where enzymatic activity and metabolite production accelerate tissue degradation and off-odors, reinforcing the importance of monitoring microbial load for food safety management. Furthermore, the findings indicate that intrinsic food properties, when combined with storage conditions, provide valuable predictive indicators for spoilage modeling. As demonstrated by Bankole and Adebajo, integrating microbial counts with environmental and intrinsic parameters enables the development of AI models capable of forecasting spoilage onset and remaining shelf-life. The dataset generated from these observations provides a reliable baseline for predictive analytics, supporting interventions that enhance food safety, optimize storage practices, and reduce unnecessary food waste.

The findings presented in Table 4.1.2 indicated that all three AI models—Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN)—effectively predicted spoilage in fish and tomato samples, with Random Forest consistently achieving the highest performance across all metrics. For fish, RF achieved 95% accuracy, 94% precision, 96% recall, 95% F1-score, and an RMSE of 1.2×10^3 CFU/g, while for tomato, accuracy was 93%, precision 92%, recall 94%, F1-score 93%, and RMSE 1.0×10^3 CFU/g. This indicates that RF was highly reliable in capturing the non-linear interactions between storage conditions, environmental parameters, and intrinsic food properties to predict microbial growth and spoilage levels. This observation aligns with the report of Adebisi, who demonstrated that ensemble learning methods such as Random Forest effectively model complex microbial dynamics in perishable foods due to their ability to handle multiple correlated features simultaneously. Similarly, Okafor and Nwachukwu reported that AI models incorporating intrinsic

and environmental data provide accurate predictions of spoilage onset and shelf-life in fresh fish and vegetables. ANN also performed well, particularly in modeling temporal patterns of microbial growth, but showed slightly higher RMSE values, reflecting minor deviations between predicted and actual microbial counts. In contrast, SVM exhibited moderately lower performance, likely due to its limited capacity to handle highly non-linear relationships inherent in microbial proliferation. These results strongly indicate that Random Forest is the most suitable model for real-time spoilage prediction, providing precise and timely forecasts that can guide storage management, reduce post-harvest losses, and improve food safety. This conclusion is supported by Bankole and Adebajo, who observed that predictive AI models enhance decision-making in perishable food supply chains by accurately forecasting microbial growth trends under varying environmental conditions.

The findings presented in Table 4.1.3 indicated that the best-performing AI model, Random Forest, accurately predicted microbial loads in fish and tomato samples stored at ambient temperature (25°C). Predicted CFU/g values closely matched the actual measurements, with prediction errors ranging from 1.1% to 2.4%, demonstrating the high precision of the model in forecasting spoilage. For fish, the model predicted 8.0×10^4 CFU/g at 24 hours and 1.18×10^6 CFU/g at 48 hours, closely aligning with observed values, while tomato predictions ranged from 5.9×10^4 CFU/g at 12 hours to 9.4×10^5 CFU/g at 24 hours, reflecting minor deviations of less than 2%. This observation aligns with the report of Adebisi, who demonstrated that AI models integrating intrinsic and environmental food parameters can reliably forecast microbial growth and spoilage in perishable foods. Similarly, Okafor and Nwachukwu reported that predictive modeling of spoilage enables early detection of microbial proliferation, allowing timely interventions to enhance food safety and reduce post-harvest losses. The low prediction errors in this study indicate that the model effectively captured the dynamics of microbial growth under varying storage conditions, confirming its suitability for real-time monitoring and practical applications in supply chain management.

The findings presented in Table 4.2 indicated that all three AI models—Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN)—effectively predicted spoilage in fish and tomato samples, with Random Forest consistently achieving the highest performance across all metrics. For fish, RF recorded 95% accuracy, 94% precision, 96% recall, 95% F1-score, and an RMSE of 1.2×10^3 CFU/g, while for tomato, accuracy was 93%, precision 92%, recall 94%, F1-score 93%, and RMSE 1.0×10^3 CFU/g. These results demonstrate RF's superior ability to capture non-linear interactions between storage conditions, environmental parameters, and intrinsic food properties. This observation aligns with the report of Adebisi, who highlighted that ensemble learning methods such as Random Forest effectively model complex microbial growth patterns in perishable foods. Similarly, Okafor and Nwachukwu noted that AI models integrating multiple predictive features provide highly reliable forecasts of spoilage onset and microbial proliferation. ANN also performed well, particularly in modeling temporal spoilage trends, but exhibited slightly higher RMSE values, indicating minor deviations from actual microbial loads. In contrast, SVM showed comparatively lower predictive accuracy, likely due to challenges in handling the non-linear and dynamic nature of microbial growth. These findings confirm that Random Forest is the most reliable algorithm for real-time spoilage prediction, enabling timely interventions to enhance food safety and reduce post-harvest losses in fish and tomato supply chains.

The findings presented in Table 4.3 indicated that the AI models, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) effectively predicted real-time spoilage in fish and tomato samples across different storage conditions. Predicted microbial loads closely matched the actual CFU/g values, with RF consistently showing the lowest prediction errors, ranging from 1.1% to 2.8%, demonstrating its high reliability for real-time monitoring. Fish stored at 25°C exhibited rapid microbial growth, yet all models captured these trends accurately, while tomato samples maintained precise predictions under both refrigerated (4°C) and ambient (25°C) conditions. This observation aligns with the report of Adebisi, who noted that integrating intrinsic food properties and environmental data into AI models enhances the accuracy of spoilage predictions in perishable foods. Similarly, Okafor and Nwachukwu reported that real-time predictive modeling allows timely interventions by forecasting microbial proliferation and spoilage onset. The consistent performance of

RF, particularly its low prediction error, confirms its suitability for practical applications in supply chain management, enabling early detection of spoilage, improved food safety, and reduced post-harvest losses. ANN and SVM also provided reliable predictions, though with slightly higher deviations, indicating their potential as complementary models depending on specific monitoring needs.

The findings presented in Table 4.4 indicated that the AI models, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) effectively contributed to reducing food waste and improving food safety in fish and tomato samples. Random Forest consistently provided the most accurate predictions of spoilage onset, with predicted times closely matching actual observations and the lowest RMSE values (1.2×10^3 CFU/g for fish, 1.0×10^3 CFU/g for tomato), enabling early detection of microbial growth and timely interventions that minimized unnecessary discard. ANN also performed well in modeling spoilage trends, though some predictions were slightly delayed, while SVM showed moderate performance, with lower accuracy and F1-scores, reflecting less precise timing of spoilage onset. This observation aligns with the report of Adebisi, who demonstrated that AI-driven real-time monitoring of perishable foods enables proactive management of storage conditions, reducing post-harvest losses and improving food safety. Similarly, Okafor and Nwachukwu reported that predictive modeling supports timely decision-making for consumption and handling of perishable products, mitigating microbial risk and optimizing shelf-life. The consistent performance of RF confirms its suitability as a reliable tool for food supply chain management, while ANN and SVM offer complementary approaches for trend prediction and moderate monitoring, respectively.

Conclusion

The findings from the study indicate that microbial growth in fish and tomato samples is highly influenced by storage temperature, with ambient conditions (25°C) accelerating spoilage compared to refrigerated storage (4°C). AI models, particularly Random Forest (RF), accurately predicted microbial load, spoilage onset, and real-time trends, outperforming Support Vector Machine (SVM) and Artificial Neural Network (ANN) across all performance metrics. Integration of food and environmental parameters with AI enabled precise, real-time monitoring, allowing early warning of microbial proliferation, timely interventions, improved food safety, and reduced food waste.

Recommendations

Based on the result of the findings, the following were recommended;

- i. Perishable foods such as fish and tomato should be stored at low temperatures to minimize microbial growth and extend shelf-life.
- ii. Food processors and retailers should adopt AI-based predictive models, especially Random Forest, to monitor spoilage and optimize storage duration.
- iii. Integration of digital sensors for continuous environmental monitoring should be implemented to provide real-time data for AI-driven spoilage prediction.
- iv. Policymakers should encourage the use of AI technologies in food supply chains to reduce post-harvest losses and enhance public health safety.

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